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Original article

Evaluation of Pavement Condition Deterioration Using Artificial Intelligence Models

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Abstract
Introduction. One of the most significant tasks facing road experts is to maintain the transport network in good condition. The process of selecting an appropriate approach to providing such condition is quite complex since it requires considering many parameters, such as the existing condition of the pavement, road category, weather conditions, traffic volume, etc. Recently, the rising trend of digitization in the industry has contributed to the use of artificial intelligence to address problems in several fields, including the bodies in charge of operational control over the status of roadways. Within the context of any control system, the main task of the control system is to carry out reliable forecasting of the operational state of the road in the medium and long term.
Materials and Methods. This study investigated the possibility of using artificial neural networks to assess existing pavement characteristics and their potential application in developing road maintenance strategies. A back-propagation neural network was implemented, trained using data from 1,614 investigated sections of the M4 "DON" highway in the road network of the Russian Federation in the period from 2014 to 2018. Several models were developed and trained using the MATLAB application, each with a different number of neurons in the hidden layers.
Results. The results of the models showed a convergence between the inferred paving state values and the actual values, as the multiple correlation coefficient (R^2) values exceeded 92 % for most of the models during all learning stages.
Discussion and Conclusions. The findings suggest that public road authorities may utilize the established models to choose the best road maintenance strategy and assign the most efficient steps to restore road bearing capacity and operation.

Keywords: artificial neural network, back-propagation algorithm, falling weight deflectometer test, pavement maintenance, pavement management system.

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Introduction. Road infrastructure is one of the resources that are vital to any community, so it is necessary to think about ways to maintain its efficiency. However, roads deteriorate over time as a result of being subjected to various deterioration mechanisms [1]. As a result, it is essential to manage these resources strategically to maximize their service life and technical indicators while also lowering maintenance costs [2].

Pavement management systems (PMS) aid in the maintenance of pavement performance at an appropriate level for use and provide a variety of financial and social advantages. Moreover, it contributes significantly to the cleanliness of the surroundings during the usage or maintenance [3]. Accordingly, if the condition of the pavement network is allowed to deteriorate, the damages will not only increase the costs of road maintenance to raise their efficiency. But, it will cause environmental harm due to emissions and traffic noise, as well as expose travelers to the hazards of automobiles travelling on rough roads [4].

Due to the significant damage caused by the deterioration of roads, transportation agencies in various countries allocate a large part of their annual budget to the maintenance or rehabilitation of these damaged roads. The importance of maintenance planning work is to choose the appropriate time and method to reduce the rate of deterioration of pavement sections according to the available budget. To reach this goal, it is required to develop models that help improve the development process and take into account the factors affecting the maintenance decision making [5].

Multi-criteria models are commonly used in complicated decision-making situations, like those involving the network-wide maintenance of road infrastructure [6]. Multi-criteria models emerge as a scientific approach for evaluating multiple alternative interventions in the framework of road rehabilitation, taking into account the properties of pavement sections [7].

It is well recognized that a pavement's surfacing behavior reflects its condition; for this reason, pavement administrations depend on knowing the value of the PCI index through the process of visual inspection of the roads periodically in order to extend the life of the pavement and improve service levels [8]. The value of the pavement condition coefficient is one of the most significant factors based on which the most appropriate method of maintenance is determined, in addition to other factors, such as weather factors and traffic volume.

Over the last two decades, it has become clear that traditional knowledge of road maintenance is not enough, and there is an urgent need to develop new methods that help collect and process data for use in pavement management [9]. Due to the rapid development in the domains of information technology and artificial intelligence networks, many opportunities have been provided to find solutions to many problems in various fields, including road engineering.

Artificial neural network models are an application of the field of artificial intelligence used to solve non-linear geometric models, such as forecasting, recognition, and estimation of different patterns [10]. Artificial neural network models mimic the human brain's ability to solve issues using previous experiences. As a result, we can use this approach for choosing the most appropriate way to maintain the road after calculating its current or future condition instead of relying on human experience and knowledge.

Artificial neural networks (ANN) review:

Many studies focused on the possibility of using the artificial neural networks approach to determine the current and future state of the pavement to using it in the development of pavement management systems and determining the method of maintenance. We will mention some of these studies as follows:

R. Kumar, et al. created a neural network model for determining the condition rating of flexible pavements depending on pavement distress data collected. The study result appeared that the neural network was able to calculate pavement condition rating accurately [11].

Hamdi, et al. built an artificial neural network model using distress data generated from a visual assessment method to determine the Surface Distress Index. The positive modeling results showed that it could be used to determine the SDI coefficient [12].

After the results of the ANN models showed superiority in predicting the values of the pavement condition, many researchers were interested in developing models that can predict the values of pavement distress as an indicator of the pavement condition.

D. T. Thube used a neural networks approach to construct four models to predict pavement defects (cracking, rut depth, roughness, and raveling) as pavement condition indicators. The small differences between the observed and calculated distress values were evidence of the model's success [13].

L. Yao, et al. used a neural network approach to construct five models that predict five indicators of pavement distress: the transverse crack index, the skid-resistance index, roughness, the rut index, and pavement surface distress. The results of the models showed an acceptable performance in predicting the condition of the pavement, with an average testing R^2 of 0.8692 [14].

A. Shtayat, et al. [15], M. Mazari and D. D. Rodriguez [16] studied the possibility of predicting the International Roughness Index (IRI) based on distress data or different pavement performance indicators, such as traffic coefficients

and structural properties of pavement through neural network models or combined with gene expression programs or regression analysis. However, the results of neural network models showed an acceptable superiority compared to other methods.

A. M. Mosa suggested a neural network-based approach for diagnosing pavement distresses and optimizing solutions for maintenance techniques suggestions. The created system supplied the optimal solutions taking into consideration technological, economic, and environmental requirements [17].

The results of the mentioned literature review showed the ability of neural network models to represent the complex and nonlinear relationship between several variables. Therefore, it can contribute to solving road engineering problems. We also note the use of most previous studies of ANN models with an inverse propagation logarithm, and we will mention a summary of them in the following section.

Description of back-propagation artificial neural networks:

The back-propagation algorithm is one of the most widely utilized algorithms of artificial neural network models. It has a high capacity and speed in processing new data after conducting several iterations for a set of data during the education stage [18, 19].

The structure of the back-propagation algorithm for artificial neural networks consists of three or more layers, including the input layer, the output layer, and one or more hidden layers, as shown in Figure 1. The function of the neurons inside the input layer is to receive data and then pass it through the hidden layers, which have the ability to examine the correlations between variables and process the data to the output layer, which provides the results by the neurons in it [20] .

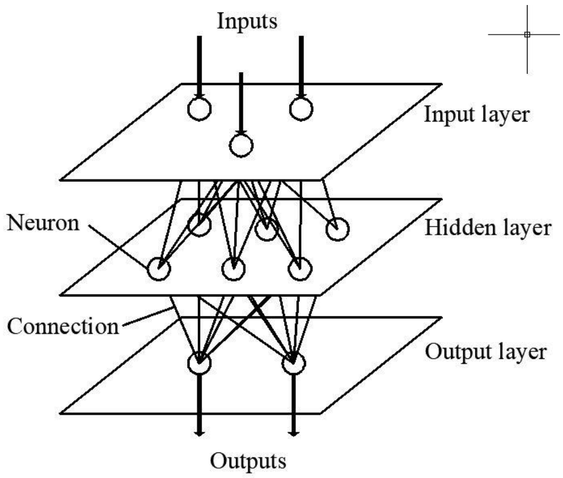


Fig. 1. Artificial Neural Network Construction Layers

In order for the neural network to perform the function assigned to it, the data must pass through three stages. The first is the process of training the network, in which it understands the effect of each variable and its relationship to other variables. Then we move on to the second stage, which is the validating process of the model, and finally, the network testing stage [21].

The back-propagation approach employs supervised learning, which implies that we supply examples data for the inputs and outputs to the network for learning [22]. The model assumes random weights for each variable and then passes the data forward to calculate the output. After calculating the difference between the computed output and the target values during the back pass, the weights are adjusted again to reduce the error rate and return the data from the output layer through the hidden layer to the input layer. The described learning process is repeated several times until the learning process is stopped when the error reaches an allowable value [19].

The weights determined during the training phase are employed in the testing process to calculate the output of a new input data set that was not used during the learning process. An evaluation of the ANN model is based on the amount of computed error.

The research scopes:

The study aims to use the field of artificial intelligence to build a model that helps engineers or decision-makers who prepare a road maintenance map to know the condition of the pavement without the need to conduct a periodic visual inspection. This reduces the dangers to individuals in charge of the examination process, as well as the effort, time, expense associated with it, and the errors that occur throughout the measuring procedure. To achieve this goal, we utilized the values of the deflection measurements coming from the falling weigh deflection test and the pavement condition index values from the Russian Road Company project for developing the M4 highway between the periods

from 2014 to 2018. We prepared a database for training and testing artificial neural network models by MATLAB software. The importance of this research is to accurately describe the future condition of the asphalt pavement to use the appropriate maintenance method to slow down the rate of asphalt deterioration.

Materials and Methods

Preparation of the database:

The data obtained for constructing the ANN model were collected from a study carried out by the Russian Road Corporation for developing the M4 highway between Moscow and Krasnodar. The available data includes inspection date, air temperature, asphalt layer thickness, base layer thickness, traffic volume, and precipitation rate and deflection values based on the falling weight deflectometer test.

The database was used to calculate three criteria that express the condition of the asphalt surface, which are the probability of success of the pavement sectors against the following three defects: fatigue, roughness, and rutting, as well as the modulus of elasticity of the pavement layers (asphalt layer, base layer, and subgrade layer) that were determined using a software package PRIMAX as input data and Regarding calculating the input parameter of “pavement surface life”, it was determined by taking the difference between the deflection survey date and the date of construction or last rehabilitation date. Also, the initial pavement condition mentioned in the same study, represented by PCI values, was used as output data to train ANN models to predict PCI values.

Calculating pavement defects using the logistic model:

Non-destructive testing is an important approach for evaluating pavement structures and is widely accepted as a reliable way of determining the structural condition of existing pavements [23]. The falling weight deflectometer (FWD) is well-known for its effectiveness in determining the structural condition of pavement and assisting in defining the best treatment option possible, which reduces the deterioration of the pavement [24, 25].

The values expressing the resistance of the pavement sections to the above three pavement defects were calculated using the logistic model equations developed by the Federal Highway Administration Long-Term Performance (LTPP).

Equations 1 and 2 show the general formula, the linear formula, that were produced from the logistic model to calculate the three distress indicators of the pavement for all sectors used in building the ANN model.

Equation (1) described the general formula of the logistic model.

$$p(event)= \frac{1}{1+ e^{-b}} \tag{1}$$

Equation (2) described the calculation formula of the exponent term in the general linear.

$$b= a_0+ a_1b_1+ a_2b_2+...+ a_nb_n \tag{2}$$

where p represents the probability of an event occurring, b represents the exponent variable and (a_0, a_1, $a_{2 \dots}$ a_n) are the constants of the variables of the linear equation.

The variables that influence pavement fatigue to determine the value of the parameter (b) are:

– D_1 denotes the deflection measured in the loading plate's midpoint;

– AADTT;

– the base layer type.

To compute the exponential component in equation (1), we utilized the variable values generated from the logistic model for pavement fatigue cracking in Table 1.

Table 1

The coefficients values utilized in the linear equation to calculate the condition of fatigue cracking

Variables (*bi*)	a_i	
I_1	154.764	a_i = coefficient values of the equation. I_1 = The utilized deflection value's mutual index
AADTT	–0.0005073	
Pavement type	0.3774	
Constant	–0.2202	

Equation (3) is used to find the variable I_1 [26].

$$I_1= \frac{1}{D_1} \tag{3}$$

The variables that influence pavement roughness to determine the value of the parameter (b) are:

– D_2 is the measured deflection value at distance 200 mm from the center of the loading plate;

– the volume of trucks in the Class 9 classification;

– the pavement surface age from construction or from the latest maintenance.

To compute the exponential component in equation (1), we utilized the variable values generated from the logistic model for pavement roughness in Table 2.

Table 2

The coefficients values utilized in the linear equation to calculate the condition of roughness distress

Variables (*bi*)	a_i	
I_2	239.849	a_i = coefficient values of the equation. I_2 = The utilized deflection value's mutual index.
Current life	–0.189	
Class 9 volume	–0.0006781	
Constant	0.8375	

Equation (4) is used to find the variable I_2 [26].

$$I_2 = \frac{1}{D_2} \tag{4}$$

The variables that influence pavement rutting to determine the value of the parameter (*b*) are:

– D3 is the recorded deflection at a distance of 300 mm from the load plate's center;

– D4 is the deflection recorded at 450 mm from the load plate's center;

– the volume of trucks in the Class 9 classification;

– average annual precipitation in the zone area (mm).

To compute the exponential component in equation (1), we utilized the variable values generated from the logistic model for pavement rutting in Table 3.

Table 3

The coefficients values utilized in the linear equation to calculate the condition of rutting distress

Variables (*bi*)	a_i	
CI_3	–0.01146	a_i = coefficient values of the equation. CI_3 = Curvature index for the ith deviations values.
Precipitation (mm)	–0.0005259	
Class 9 volume	–0.0007688	
Constant	2.6586	

Equation (5) is used to find the variable CI_3 [26].

$$CI_3 = D_3 - D_4 \tag{5}$$

Initial Database for Neural Networks

The database for entry in the neural network is comprised of a set of input data and a set of output data. The input data are the measured values of the following parameters: pavement surface life, asphalt layer thickness, base layer thickness, p(fatigue), p(roughness), p(rutting), the elastic modulus of (surface layer, base layer, and subgrade layer) shown as their mean value for an individual pavement segment. The model outputs are the pavement condition index values for the pavement sections that are available in the database. The goal of this database is the preparation and sorting of data in a format appropriate for entering it into the neural network.

Application of ANN

For the objective of this study, artificial neural networks with back-propagation algorithms and different numbers of neurons (8, 9, 10, 11, 12, 13, and 14) in two hidden layers were applied using the MATLAB software. The total quantity of inspection data utilized in the construction of the ANN model was 1,614 representing 51 different sectors along the M4 highway. The data used in the training process included the minimum and maximum values of the variables to increase the efficiency of the models.

The database was divided into three groups: a large amount of database in which the neural network conducts the learning process on 70 % of the randomly selected data; the second group represents the validation process with 15 % of the database; the remaining 15 % of the data for the third group was for testing the developed network. Figure 3 shows the configuration for one of the created neural networks during training.

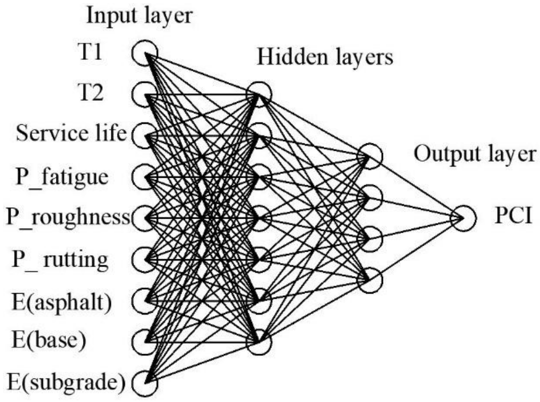


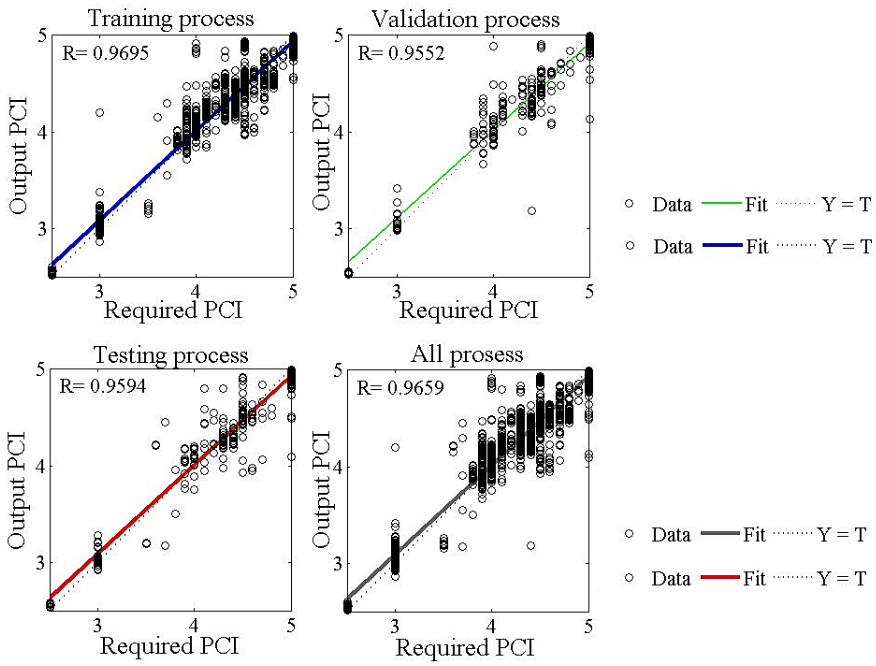
Fig. 2. The Applied ANN Model Structure

Each of the input parameters is represented by one of the nine neurons in the input layer. Eleven neurons are applied in the hidden layers, split into seven neurons in the first hidden layer and four neurons in the second layer. The output layer includes one neuron that represents the number of output data. The previous figure shows the direction of data transmission from the input layer to the output layer through two hidden layers and vice versa to correct the error rate in the output values until the permissible limit is reached.

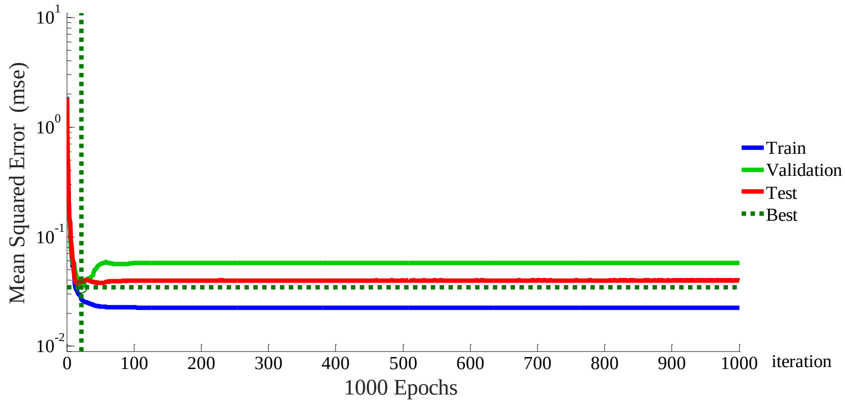
Several numbers of layers and neurons inside the hidden layers were applied to increase the performance of the developed network. The training procedure was repeated several times until the optimal model that accurately expressed the relationship between the input and output data was found. The effectiveness of the trained models were compared using statistical analysis of the outputs, which were represented by the mean absolute error (MAE), and coefficient of multiple correlations (R^2), Root Mean Square Error (RMSE), and mean absolute percentage deviation (MARD).

Results. After the learning step, the neural network was subjected to testing. In the testing process, weights were fixed to values adopted at the end of the learning process. A new group of input and output data was offered to the network. Network output results were compared with required output and statistically analyzed.

The following regression and performance plots illustrate the output of the network models concerning training, validation, and test sets. Throw the training process, the optimal values of the network elements were carried out after 1,000 repetitions with (MSE = 0.0224). The best validation performance of the demonstrated model was 0.0344, which was achieved after 22 repetitions for the model with structure (9–10–1), as shown in Figure 3 (*a*, *b*). The optimal values of the network elements were carried out after 1,000 repetitions with (MSE = 0.0234). The best validation performance of the demonstrated model was 0.03171, which was achieved after 11 repetitions for the model with structure (9–11–1), as shown in Figure 4 (*a*, *b*). The low value of MSE of the selected models indicates that pavement conditions of roads in the same domain may be anticipated more accurately.

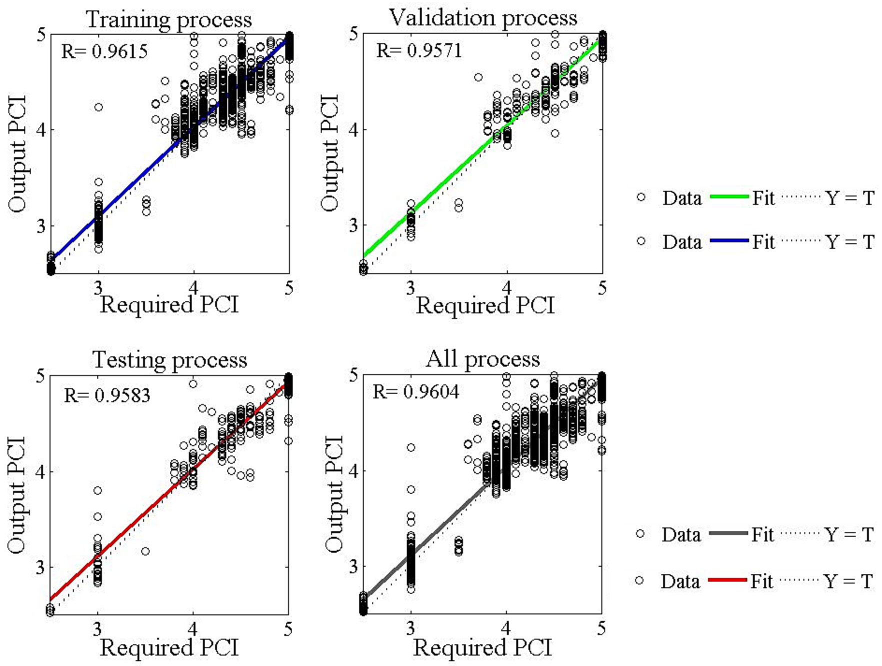


a)

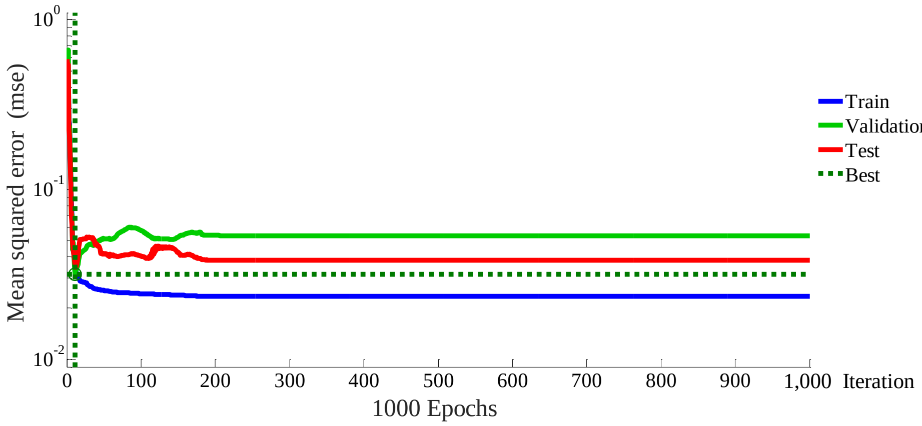


b)

Fig. 3. Results of training an ANN model with a structure (9–10–1): *a* — regression graphs; *b* — performance chart



a)



b)

Fig. 4. Results of training an ANN model with a structure (9–11–1): *a* — regression graphs; *b* — performance chart

According to the output results, notice a high correlation coefficient between the outcomes of the neural network computation and the needed outputs. There is a significant correlation between them where most of the data falls near a

45-degree line. As shown in the previous regression charts displayed for all stages, whether training, validation or testing phases, the correlation coefficients (R) values are greater than 95% for all stages, indicating the quality of the generated models and the ability to estimate the outputs correctly.

Evaluation of Artificial Neural Network:

The created ANN model may be saved as a MATLAB file once the training procedure is completed, and the desired accuracy is achieved. We can use it to do a forward computation and forecast pavement conditions for maintenance and rehabilitation purposes.

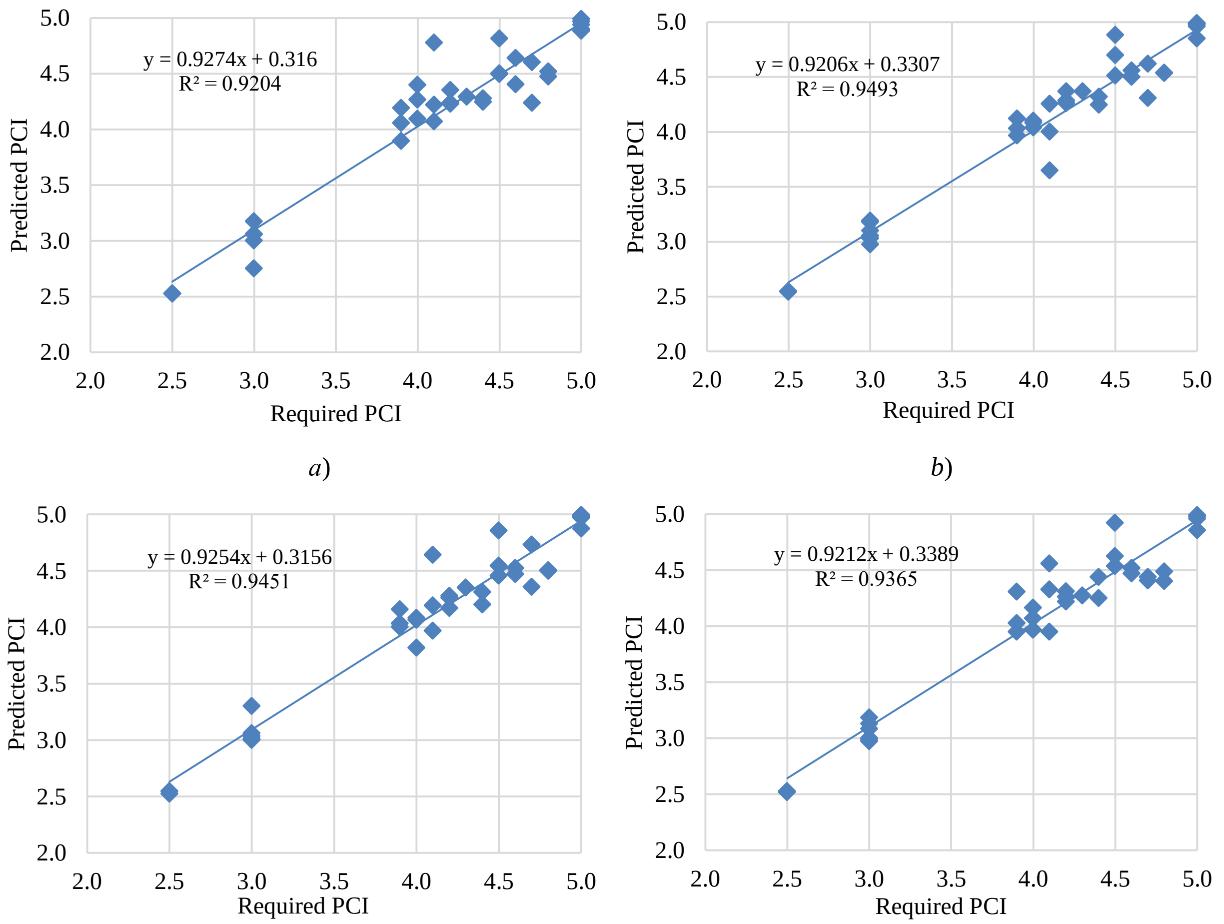
For this purpose, a new dataset of 37 sections was assigned to asphalt pavement to evaluate the ability of the developed neural networks used in the previous section to predict the output values. In this step the models were defined by input data for the specified parameter values, which were: (asphalt layer thickness, base layer thickness, surface life, p (fatigue), p (roughness), p (rutting), E (asphalt), E (base), and E (subgrade)). As a result, the created networks were able to anticipate output data (pavement condition index- PCI) based on early experience.

The criteria for choosing the best iteration for every model were: mean absolute error (MAE), coefficient of multiple correlations (R^2), Root Mean Square Error (RMSE), and mean absolute percentage deviation (MARD) of the estimates (PCI). They ensured that the predicted values were within reasonable data limits, as shown in Table 4. Figure 6 (*a*, *b*, *c*, *d*, *e*, and *f*) presents the relationship between the prediction results of the best iteration for every model with different numbers of neurons in the hidden layers, and the target output results.

Table 4

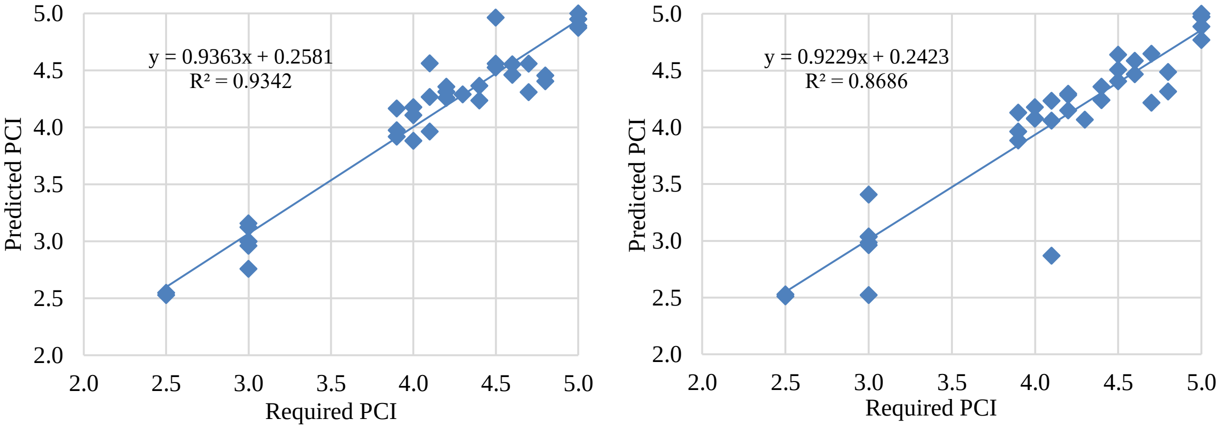
Statistical assessment of the created models' output (forecasted results)

Statistical comparison criteria	Pavement Condition Index – PCI						
	8n	9n	10n	11n	12n	13n	14n
MAE	0.1415	0.1242	0.1185	0.1317	0.1362	0.1594	0.1190
R^2	0.9204	0.9493	0.9451	0.9365	0.9342	0.8686	0.9483
RMSE	0.2058	0.1651	0.1710	0.1840	0.1862	0.2765	0.1666
MARE	3.4478	3.0430	2.8738	3.1545	3.2909	3.9488	2.9649



a) *b*)

c) *d*)



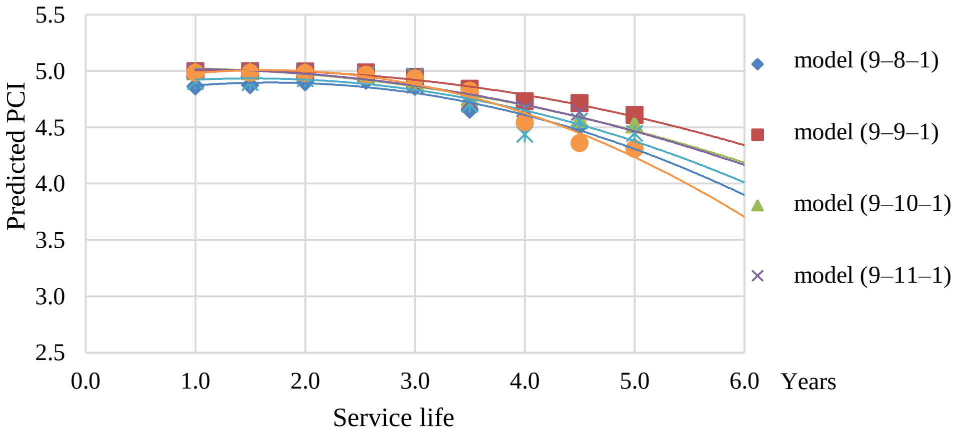
e) *f*)

Fig. 5. Relation between actual PCI and predicted PCI for all ANN models: *a* — model with 8 neurons; *b* — model with 9 neurons; *c* — model with 10 neurons; *d* — model with 11 neurons; *e* — model with 12 neurons; *f* — model with 13 neurons

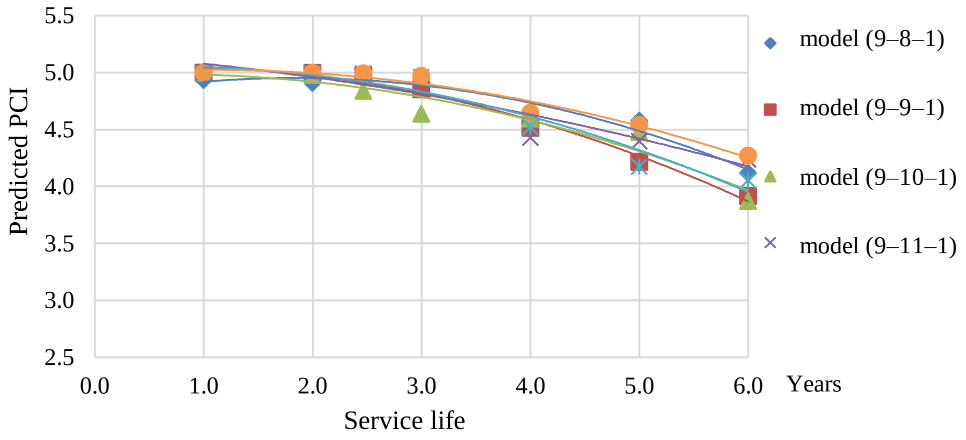
Looking at the results of the statistical analysis of the outputs of the developed models represented in Table 4 and Figure 5 (*a-f*), we find that they have an acceptable ability to predict the condition of pavement based on the variables that were used in training the models. Also, notice that the best results were for two models with the structure (9–9–1) and (9–10–1), as they had the highest coefficient of multiple correlations (R^2), which is 0.9493, 0.9451, as well as the lowest values of MAE, RMSE, and MARE.

Evaluation of pavement deterioration via ANN model:

To recognize that the developed neural network models can help in predicting the rate of pavement deterioration, the idea arose to select several asphalt sectors and determine the effect of changing the operational life on the condition of each sector. To achieve this goal, each model defined the input values for each sector and fixed them, except for one variable, which was the operational life. Then we left the opportunity for the models to calculate the output values based on their previous experience. The sectors that were subjected to this experiment were numbers 504, 1227, 430, and 544, as shown in Figures. 6 (*a*, *b*, *c*, and *d*).



a)



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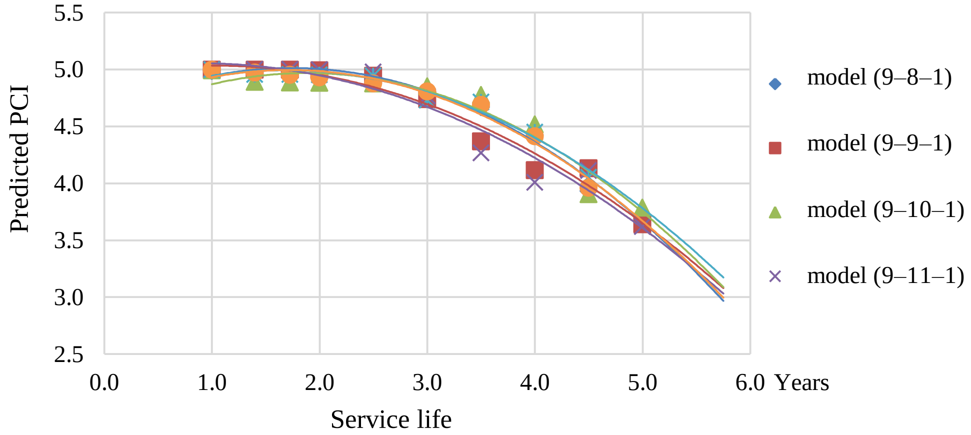

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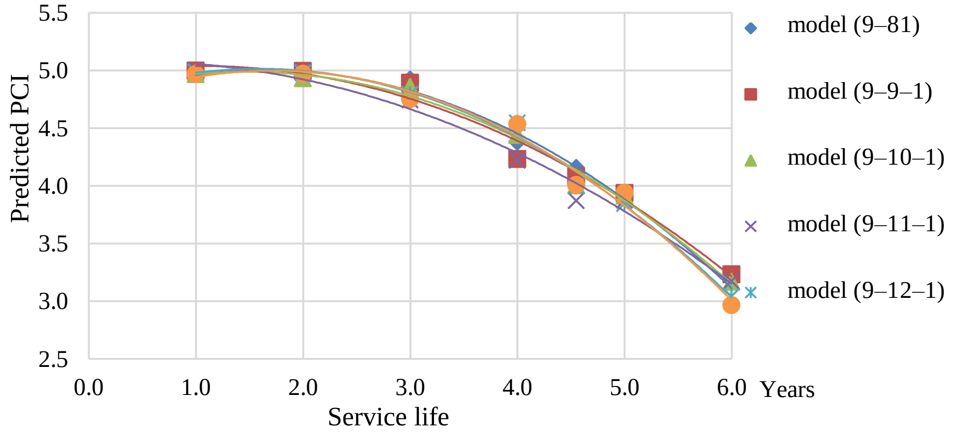

d)

Fig. 6. Pavement sections deteriorations against service life: *a* — deterioration of section no. 504; *b* — deterioration of section no. 1227; *c* — deterioration of section no. 430; *d* — deterioration of section no. 544

It is clear from the previous figures that the developed models have the ability to predict the condition of the asphalt as a result of the change in the service life. Where the value of the PCI reduces as the operational life increases, which is consistent with what happens in the field.

This research may help those in charge of developing a road maintenance plan in order to limit the deterioration of the pavement condition by anticipating the pavement condition in advance and intervening promptly by choosing the appropriate treatment method in proportion to the capabilities available to the authority entrusted with this matter.

Discussion and Conclusions. To achieve the objectives of this research, artificial neural network techniques were used to construct condition data deterioration models for pavement surfaces to assist decision-makers to choose the most efficient pavement maintenance solutions. Artificial neural networks (ANN) were utilized together with back-propagation algorithms to train the forecasting models for selecting appropriate options for treatment based on the value of the pavement condition index (PCI). A wide range of 1,614 cases of pavement condition description were provided

from previous investigations for various sectors of the Russian highway network to use as a database helping in creating the developed ANN models. Using MATLAB software, a large number of models with different numbers of neurons in the hidden layers were established, trained, and the results validated. The results of the models were studied, and the following conclusions were made:

– ANN models showed their ability to represent the nonlinear relationship between a large number of variables and the pavement condition coefficient with high accuracy, as indicated by the high value of the multiple correlation coefficient (R^2) for all stages of model learning (training, validation, and testing).

– According to models' validation, the variations between the actual PCI values and the predicted output results of the models were close to each other.

– Evaluation of models generated with different numbers of neurons in the hidden layers showed that they all assumed close patterns as well as similar flows of surface deterioration rates.

– The developed models save a lot of time and effort to determine the condition of the pavement and reduce the risks for the examiners compared to the visual examination method due to its dependence on the results of the dropped pregnancy test.

– The obtained results suggested that decision-makers might use the created modeling to optimize maintenance or rehabilitation methods for the most impacted roads to lower the rate of degradation based on available resources.

References

1. Schnebele E, Tanyu BF, Cervone G, et al. Review of Remote Sensing Methodologies for Pavement Management and Assessment. European Transport Research Review. 2015;7:1–19. https://doi.org/10.1007/s12544-015-0156-6

2. Jianyou Zhao, Xiaoyu Fu, Yunjiao Zhang J. Research on Risk Assessment and Safety Management of Highway Maintenance Project. Procedia Engineering. 2016;137:434–441. https://doi.org/10.1016/j.proeng.2016.01.278

3. Santero NJ, Horvath A. Global Warming Potential of Pavements. Environmental Research Letters. 2009;4:034011. https://doi.org/10.1088/1748-9326/4/3/034011

4. Schlegel T, Puiatti D, Ritter H-J, et al. The Limits of Partial Life Cycle Assessment Studies in Road Construction Practices: A Case Study on the Use of Hydrated Lime in Hot Mix Asphalt. Transportation Research Part D: Transport and Environment. 2016;48:141–160. https://doi.org/10.1016/j.trd.2016.08.005

5. Ameri M, Jarrahi A. An Executive Model for Network-Level Pavement Maintenance and Rehabilitation Planning Based on Linear Integer Programming. Journal of Industrial and Management Optimization. 2020;16:795–811. http://dx.doi.org/10.3934/jimo.2018179

6. Karleuša B, Dragičević N, Deluka-Tibljaš A. Review of Multicriteria-Analysis Methods Application in Decision Making about Transport Infrastructure. Građevinar. 2013;65:619–631. https://doi.org/10.14256/JCE.850.2013

7. Dabous SA, Zeiada W, Zayed T, et al. Sustainability-Informed Multi-Criteria Decision Support Framework for Ranking and Prioritization of Pavement Sections. Journal of Cleaner Production. 2020;244:118755. https://doi.org/10.1016/j.jclepro.2019.118755

8. Setyawan A, Nainggolan J, Budiarto A. Predicting the Remaining Service Life of Road Using Pavement Condition Index. Procedia Engineering. 2015;125:417–423. https://doi.org/10.1016/j.proeng.2015.11.108

9. Chengjia Han, Tao Ma, Guangji Xu, et al. Intelligent Decision Model of Road Maintenance Based on Improved Weight Random Forest Algorithm. International Journal of Pavement Engineering. — 2022. — Vol. 23. — P. 985–997. https://doi.org/10.1080/10298436.2020.1784418

10. Abiodun OI, Jantan A, Omolara AE, et al. State-of-the-Art in Artificial Neural Network Applications: A Survey. Heliyon. 2018;4:e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

11. Kumar R, Suman SK, Prakash G. Evaluation of Pavement Condition Index Using Artificial Neural Network Approach. Transportation in Developing Economies. 2021;7:1–15. https://doi.org/10.1007/s40890-021-00130-7

12. Hamdi, Hadiwardoyo SP, Correia AG, et al. Prediction of Surface Distress Using Neural Networks. AIP Conference Proceedings. 2017;1855:040006. https://doi.org/10.1063/1.4985502

13. Thube DT. Artificial Neural Network (ANN) Based Pavement Deterioration Models for Low Volume Roads in India. International Journal of Pavement Research and Technology. 2012;5:115–120.

14. Lingyi Yao, Qiao Dong, Jiwang Jiang, et al. Establishment of Prediction Models of Asphalt Pavement Performance Based on a Novel Data Calibration Method and Neural Network. Transportation Research Record. 2019;2673:66–82. https://doi.org/10.1177/0361198118822501

15. Shtayat A, Moridpour S, Best B, et al. An Overview of Pavement Degradation Prediction Models. Journal of Advanced Transportation. 2022;2022:7783588. https://doi.org/10.1155/2022/7783588

16. Mazari M, Rodriguez DD. Prediction of Pavement Roughness Using a Hybrid Gene Expression Programming-Neural Network Technique. Journal of Traffic and Transportation Engineering (English Edition). 2016;3:448–455. https://doi.org/10.1016/j.jtte.2016.09.007

17. Mosa AM. Neural Network for Flexible Pavement Maintenance and Rehabilitation. Applied Research Journal. 2017;3:114–129.

18. Ceylan H, Gopalakrishnan K, Bayrak MB. Neural Networks Based Concrete Airfield Pavement Layer Moduli Backcalculation. Civil Engineering and Environmental Systems. 2008;25:185–199. https://doi.org/10.1080/10286600701838667

19. Elshamy MM, Tiraturyan AN, Uglova EV, et al. Comparison of Feed-forward, Cascade-forward, and Elman Algorithms Models for Determination of the Elastic Modulus of Pavement Layers. In: Proc. 2021 4th International Conference on Geoinformatics and Data Analysis. 2021. P. 46–53. https://doi.org/10.1145/3465222.3465235

20. Ceylan H, Gopalakrishnan K, Bayrak MB, et al. Noise-Tolerant Inverse Analysis Models for Nondestructive Evaluation of Transportation Infrastructure Systems Using Neural Networks. Nondestructive Testing and Evaluation. 2013;28:233–251. https://doi.org/10.1080/10589759.2012.742084

21. Issa A, Samaneh H, Ghanim M. Predicting Pavement Condition Index Using Artificial Neural Networks Approach. Ain Shams Engineering Journal. 2022;13:101490. https://doi.org/10.1016/j.asej.2021.04.033

22. Taher KA, Jisan BMY, Rahman MM. Network Intrusion Detection Using Supervised Machine Learning Technique with Feature Selection. In: Proc. 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST) – IEEE. 2019. P. 643–646. https://doi.org/10.1109/ICREST.2019.8644161

23. García JAR, Castro M. Analysis of the Temperature Influence on Flexible Pavement Deflection. Construction and Building Materials. 2011;25:3530–3539. https://doi.org/10.1016/j.conbuildmat.2011.03.046

24. Donovan P, Tutumluer E. Falling Weight Deflectometer Testing to Determine Relative Damage in Asphalt Pavement Unbound Aggregate Layers. Transportation Research Record. 2009;2104:12–23. http://dx.doi.org/10.3141/2104-02

25. Elshamy MMM, Tiraturyan AN, Uglova EV, et al. Development of the Non-destructive Monitoring Methods of the Pavement Conditions via Artificial Neural Networks. Journal of Physics: Conference Series. 2020;1614:012099. https://doi:10.1088/1742-6596/1614/1/012099

26. Stubstad R, Carvalho R, Briggs R, et al. Simplified Techniques for Evaluation and Interpretation of Pavement Deflections for Network-Level Analysis: Guide for Assessment of Pavement Structure Performance for PMS Applications. Turner-Fairbank Highway Research Center; 2012. P. 34. — URL: https://www.fhwa.dot.gov/publications/research/infrastructure/pavements/ltpp/12025/12025.pdf

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Conflict of interest statement

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